

# Coupling Coordination Between Land Use Intensity and Landscape Ecological Risk in Xinjiang

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## Abstract

Xinjiang is located in the arid region of northwestern China. Against the background of the Belt and Road Initiative and southward development, the contradiction between its socioeconomic development and ecological protection has attracted considerable attention. Based on three phases of land-use data for Xinjiang from 2003 to 2023, this study calculated the appropriate spatial grain and extent for analyzing land-use intensity and landscape ecological risk. On this basis, the land-use intensity, landscape ecological risk index, and their coupling coordination degree were calculated, and the spatiotemporal variation characteristics of the coupling coordination degree were analyzed. The results show that: (1) The appropriate spatial grain and extent for assessing land-use intensity and landscape ecological risk in Xinjiang are 80 m and 10.5 km. (2) Areas with high land-use intensity, low landscape ecological risk, and high coupling coordination degree are mainly concentrated on the northern slope of the Tianshan Mountains, the Ili River Valley, and the oasis areas of the Taklimakan Desert, where human activities are frequent. Land-use intensity and landscape ecological risk show increasing and decreasing trends, respectively, while the coupling coordination degree first decreases and then increases, remaining overall below 0.7. The areas of severe imbalance and primary coordination gradually decrease, whereas the areas of mild imbalance and good coordination gradually increase. (3) The high-high clustering areas of coupling coordination degree present an “E”-shaped distribution pattern, with higher values in the northwest and lower values in the southeast. Changes in landscape ecological risk are greater than those in land-use intensity across different coupling coordination type zones. (4) Socioeconomic factors have stronger explanatory power than natural factors, among which GDP and nighttime light have the most significant explanatory power. Regional coupling coordination degree is influenced by natural endowments, the economy, and policies, with the most pronounced changes occurring in the Corps and the prefectures and cities of southern Xinjiang.

## Full Text

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## Coupling Coordination Between Land Use Intensity and Landscape Ecological Risk in Xinjiang

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**Abstract:** Xinjiang is located in the arid region of northwestern China. Against the background of the promotion of the Belt and Road Initiative and southward development, the contradiction between its socioeconomic development and ecological protection has attracted considerable attention. Based on three periods of land-use data for Xinjiang from 2003 to 2023, this study calculated the appropriate spatial grain and extent for analyzing land use intensity and landscape ecological risk. On this basis, the land use intensity index, the landscape ecological risk index, and the coupling coordination degree between the two were calculated, and the spatiotemporal variation characteristics of the coupling coordination degree were then analyzed. The results show that: (1) the appropriate spatial grain and extent for evaluating land use intensity and landscape ecological risk in Xinjiang are 80 m and 10.5 km, respectively. (2) Areas with high land use intensity, low landscape ecological risk, and high coupling coordination degree are mainly concentrated in regions with frequent human activities, including the northern slope of the Tianshan Mountains, the Ili River Valley, and the oasis areas of the Taklamakan Desert. Land use intensity and landscape ecological risk show increasing and decreasing trends, respectively; the coupling coordination degree first decreases and then increases, remaining overall below 0.7. The areas of severe imbalance and primary coordination gradually decrease, while the areas of mild imbalance and good coordination gradually increase. (3) The high-high agglomeration areas of coupling coordination degree exhibit an “E”-shaped distribution pattern, with higher values in the northwest and lower values in the southeast. In different coupling-coordination-type zones, changes in landscape ecological risk are greater than changes in land use intensity. (4) Socioeconomic factors have stronger explanatory power than natural factors, among which GDP and nighttime light have the most significant explanatory power. Regional coupling coordination degree is influenced by natural endowments, the economy, and policies, with the most obvious changes occurring in the Xinjiang Production and Construction Corps and the prefectures and cities of southern Xinjiang.

**Keywords:** scale effect; land use intensity; landscape ecological risk; coupling coordination; spatial heterogeneity; geographic detector

Land use intensity (LUI) represents the comprehensive status of current land use[1] and can reflect the characteristics of human utilization of land as well as patterns of economic development. There are two methods for assessing land use intensity: system construction and index calculation. The former involves complex indicator construction and difficulty in data acquisition[2], and was mainly used in early studies in fields such as agriculture and urban studies. The latter is formed by combining scores for different land-use types[3], simplifying the evaluation process, and has therefore been widely adopted[4-5]. Landscape ecological risk (LER) refers to the adverse consequences that may arise from interactions

between landscape patterns and ecological processes under the influence of natural or anthropogenic factors[6], and can reveal changes in ecological security caused by human socioeconomic activities. Methods for assessing landscape ecological risk mainly include those based on risk sources/sinks and those based on landscape patterns[6-7]. The landscape-pattern-based method breaks away from the traditional ecosystem assessment model of “risk-source identification—receptor analysis—exposure and hazard” [8], directly uses land-use data for assessment, and is simpler in method and more unified in standards; thus, it has been widely used[9-11]. Although analyses of land use intensity and landscape ecological risk directly based on land-use data are now widely applied in practice, relatively few studies have analyzed the relationship between changes in the two and regional development patterns, or evaluated the outcomes of ecological construction, from the perspective of the socioeconomic development and ecological security represented behind assessments of land use intensity and landscape ecological risk.

Coupling degree can simulate the extent of mutual influence among multiple systems[12]. The concept originated in physics[13] and was later widely introduced into the social sciences, but it cannot reflect the level of coordinated development between two systems. Coupling coordination degree (CCD) remedies the deficiencies of the coupling-degree model[14]; because of its clear meaning and simple calculation, it has been widely applied in geographical research[15-16]. Land-cover change caused by human activities promotes changes in land use intensity and landscape ecological risk. Disorderly development inevitably leads to increases in land use intensity and landscape ecological risk, whereas scientific planning and ecological protection reduce them. Changes in the two must therefore involve an interactive relationship, causing coupling coordination to exhibit certain patterns in time and space. Based on this characteristic, using coupling coordination degree to measure regional economic development and ecological security construction in terms of

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the relationship is feasible.

As a typical representative of the arid regions of northwestern China, Xinjiang has a fragile local ecosystem. Against the backdrop of the “Belt and Road” Initiative and the strategy of southward development, rapid economic growth and accelerated land-use change have exerted certain pressure on the local ecology. Assessing the coupling relationship between land use and ecological security in Xinjiang can reveal the evolutionary characteristics of land-use intensity and landscape ecological risk, identify driving factors, and provide a scientific ba-

sis for regional development planning and policy formulation. Therefore, this study uses three periods of land-use data for Xinjiang from 2003 to 2023 to evaluate land-use intensity and landscape ecological risk; then applies a coupling coordination degree model to explore the spatiotemporal characteristics of coupling coordination between the two; and finally uses the geographical detector and statistical methods to analyze the driving factors of changes in coupling coordination degree and the developmental differences among prefecture-level cities, prefectures, autonomous prefectures, and corps cities, thereby providing a reference for Xinjiang's future green and sustainable development.

# 1 Overview of the Study Area, Data Sources, and Research Methods

## 1.1 Overview of the Study Area

The Xinjiang Uygur Autonomous Region ( $34^{\circ}25' \sim 48^{\circ}10'N$ ,  $73^{\circ}40' \sim 96^{\circ}18'E$ ) is located in the inland area of northwestern China, with a total area of approximately  $166.49 \times 10^4 \text{ km}^2$ . It is China's largest provincial-level administrative region by area (Fig. 1). Its terrain follows the basic pattern of "three mountain ranges enclosing two basins": the Altai Mountains lie in the north, the Kunlun Mountains in the south, and the Tianshan Mountains traverse the central part, dividing the region into Northern Xinjiang, Southern Xinjiang, and Eastern Xinjiang. Xinjiang has a typical temperate continental arid climate, with scarce precipitation and strong evaporation. Annual precipitation is approximately 154.8–170.6 mm, and the spatiotemporal distribution of water resources is extremely uneven, leaving the ecosystem fragile. Xinjiang administers 4 prefecture-level cities, 5 prefectures, 5 autonomous prefectures, and 12 county-level cities directly under the autonomous region. The population is mainly concentrated in the oasis belts along the margins of the Junggar Basin and the Tarim Basin. Water for production and daily life depends heavily on inland rivers supplied by glacier meltwater. Land use in the region is dominated by unused land, accounting for more than 65%, while cultivated land and construction land together account for about 7%; land desertification is a relatively prominent problem. Against the background of the advancement of the "Belt and Road" construction and the southward development strategy, the intensity of human activities has continued to increase, and socioeconomic development has accelerated, resulting in significant changes in land surface cover, increased land-use intensity, and obvious impacts on the regional ecological environment.

## 1.2 Data Sources

This study uses three periods of land-use data from 2003 to 2023, as well as driving-factor data including settlements, roads, GDP, population density, nighttime lights, elevation, slope, snow-cover days, NDVI, potential evapotranspiration, precipitation, air temperature, and water systems. The land-use data

are annual land-cover classification products with 30 m resolution from the Resource and Environment Science and Data Center (<https://zenodo.org/>); settlement, road, and water-system data are vector datasets from the National Catalogue Service for Geographic Information Resources (<https://www.webmap.cn>); population density data are based on the Gridded Population of the World dataset (<http://sedac.ciesin.columbia.edu/data>), with annual raster data at 1 km resolution; GDP data are provided by the Resource and Environmental Science and Data Center (<https://www.resdc.cn>), with a spatial resolution of 1 km and annual updates; nighttime-light data are annual global nighttime-light datasets at 1 km resolution from Harvard Dataverse (<https://dataverse.harvard.edu>); air-temperature and precipitation data are annual 1 km resolution climate data from the Resource and Environmental Science and Data Platform (<http://www.resdc.cn>); NDVI data are obtained through Earthdata Search (<https://search.earthdata.nasa.gov/>) as annual products at 1 km resolution; elevation data are from the 90 m resolution digital elevation model provided by the Geospatial Data Cloud (<http://www.gscloud.cn>); snow-cover days are provided by the National Cryosphere Desert Data Center (<http://www.ncdc.ac.cn/portal/>) as a 1 km resolution annual time series; and potential evapotranspiration data are obtained based on the Google Earth Engine platform, with a spatial resolution of 1 km.

All data were uniformly converted to a projected coordinate system. Land-use data were classified into six categories: cultivated land, forest land, grassland, water bodies, construction land, and unused land. Vector data such as rivers, settlements, and roads were converted into 1 km raster data using Euclidean distance analysis, and were then divided into five classes at intervals of 10 km, 20 km, 40 km, and 80 km. Other driving factors were uniformly divided into five classes using the natural breaks method based on 2003 as the baseline. Because high-value areas of nighttime lights and population density are mainly concentrated in urban areas, directly applying the natural breaks method would result in very few data in some categories, making the geographical detector analysis results insignificant; therefore, moderate adjustments were made on the basis of the natural breaks method.

## 1.3 Research Methods

### 1.3.1 Area Information Loss and Area Information Entropy

After grain-size conversion, a certain loss of area information occurs in the study area, thereby affecting the analysis results. Therefore, it is necessary to evaluate the loss of area for landscape types in order to determine the optimal spatial grain size. This paper uses the area information loss index and the area information entropy method to calculate the optimal spatial grain size. The formulas are as follows:

$$L = \sqrt{\frac{1}{n} \sum_{i=1}^n \frac{A_{ai} - A_{bi}}{A_{bi}}} \times 100\% \quad (1)$$

$$E = - \sum_{i=1}^n p_i \cdot \log(p_i) \quad (2)$$

In the formulas:  $L$  is the landscape area information loss index;  $E$  is the area information entropy;  $A_{ai}$  is the area of landscape type  $i$  after grain-size conversion ( $\text{km}^2$ );  $A_{bi}$  is the landscape type  $i$  ...

*Text visible in Fig. 1:* Baiyang City; Tacheng Prefecture; Beitun City; Altay Prefecture; Huaynghe City; Changji; Hui Autonomous Prefecture; Wujiaqu City; Karamay City; Shuanghe City; Bortala Mongol Autonomous Prefecture; Kokdala City; Ili; Bole City; Shihezi City; Urumqi City; Turpan City; Hami City; Xinxing City; Aksu Prefecture; Alar City; Bayingolin Mongol Autonomous Prefecture; Tiemenguan City; Kizilsu Kirgiz Autonomous Prefecture; Tumxuk City; Kashgar Prefecture; Kunyu City; Hotan Prefecture.

*Legend:* national boundary; undemarcated national boundary; provincial boundary; prefecture/state boundary. Elevation/m: 7396 to  $-167$ . Scale: 0-220 km.

*Note:* The base map was prepared using the standard map from the National Platform for Common Geospatial Information Services, with map approval number GS(2024)0650; the boundaries of the base map were not modified. The same applies below.

### Fig. 1 Schematic diagram of the study area

area before granularity conversion ( $\text{km}^2$ );  $p_i$  denotes the ratio of the area of each type to the total area; and  $n$  is the number of landscape types. A larger  $L$  indicates greater changes in the areas of the various landscapes after granularity conversion, greater loss of area information, and poorer accuracy; a smaller  $E$  indicates greater loss of area information.

### 1.3.2 Semivariogram

Geostatistical analysis can be used to describe the spatial heterogeneity patterns of regional variables and to quantitatively analyze changes in spatial patterns before and after spatial-scale conversion. Semivariogram fitting was performed for the landscape ecological risk index and land-use intensity index at different spatial scales. Fitting parameters, such as the nugget-to-sill ratio and fitting accuracy, were used to analyze the spatial variation characteristics of landscape ecological risk and land-use intensity at different spatial scales, thereby identifying the most suitable spatial scale. The nugget-to-sill ratio refers to the ratio of the nugget value to the partial sill; the smaller it is, the more suitable the current spatial scale is for attribute analysis. The closer the root mean square

is to 0 and the closer the standardized root-mean-square error is to 1, the better the fitting result. The semivariogram formula is as follows:

$$\gamma(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} [Z(x_i + h) - Z(x_i)]^2 \quad (3)$$

where  $\gamma(h)$  is the semivariogram;  $N(h)$  is the number of sample pairs separated by vector  $h$ ; and  $Z(x_i + h)$  and  $Z(x_i)$  are the values of the regionalized variable  $Z$  at points  $x_i + h$  and  $x_i$ , respectively.

### 1.3.3 Land-use intensity index

The evaluation of land-use intensity referred to the literature [17] and, in combination with the actual conditions of the study area, assigned values of 0.01, 0.01, 0.05, 0.03, 0.2, and 0.7 to water bodies, unused land, grassland, forestland, cultivated land, and construction land, respectively. The comprehensive calculation formula is as follows:

$$\text{LUI} = \sum_{i=1}^n \frac{S_i}{\sum_{i=1}^n S_i} \times D_i \quad (4)$$

where LUI is the land-use intensity index in the evaluation unit;  $D_i$  is the assigned land-use intensity value for land-use type  $i$ ; and  $S_i$  is the area of land-use type  $i$  ( $\text{km}^2$ ). The land-use intensity evaluation results were based on natural inter-

divided into five levels by the natural breaks method.

### 1.3.4 Landscape ecological risk index

This paper uses the landscape ecological risk index to evaluate landscape ecological risk. The calculation formulas are:

$$\text{LER}_k = \sum_{i=1}^n \frac{A_{ki}}{A_k} \times R_i \quad (5)$$

$$R_i = E_i \times V_i \quad (6)$$

$$E_i = aC_i + bN_i + cF_i \quad (7)$$

where:  $\text{LER}_k$  is the LER index in the  $k$ -th risk assessment unit;  $A_{ki}$  is the area of the  $i$ -th landscape type in the  $k$ -th risk assessment unit ( $\text{km}^2$ );  $A_k$  is the total landscape area in the  $k$ -th risk assessment unit ( $\text{km}^2$ );  $n$  is the total number of

risk assessment units; and  $R_i$  is the landscape loss degree index, expressed as the product of landscape vulnerability  $V_i$  and landscape disturbance  $E_i$ . Landscape vulnerability represents the susceptibility of the internal landscape structure to damage when subjected to external disturbance. In combination with the literature [11] and regional characteristics, grassland, woodland, water bodies, cultivated land, construction land, and bare land were assigned values of 4, 2, 5, 3, 1, and 6, respectively. Landscape disturbance represents the degree to which the landscape pattern is disturbed by human activities, and is composed of landscape fragmentation  $C_i$ , landscape separation  $N_i$ , and landscape fractal dimension  $F_i$ . The weights  $a$ ,  $b$ , and  $c$  for  $C_i$ ,  $N_i$ , and  $F_i$ , respectively, were assigned values of 0.5, 0.3, and 0.2 with reference to studies of typical regions in Xinjiang [9, 18–20]. The landscape ecological risk assessment results were classified into five levels using the natural breaks method.

### 1.3.5 Coupling coordination degree model

The coupling coordination degree model can quantify and evaluate whether good interaction and healthy development have formed between systems. When the values of the two systems are higher and closer to each other, the coupling coordination degree is higher. The coupling coordination degree is calculated as follows:

$$G = 2\sqrt{\frac{(U_1 \times U_2)}{(U_1 + U_2)^2}} \quad (8)$$

$$T = \alpha U_1 + \beta U_2 \quad (9)$$

$$\text{CCD} = \sqrt{G \times T} \quad (10)$$

where: CCD is the coupling coordination degree;  $G$  is the coupling degree between systems, reflecting the degree of mutual embedded linkage between the systems;  $T$  is the comprehensive coordination index of the two systems—land use intensity and landscape ecological risk—reflecting the weighted average level of the subsystems;  $U_1$  and  $U_2$  represent the normalized land use intensity and landscape ecological risk subsystems, respectively; and  $\alpha$  and  $\beta$  are both set to 0.5.

### 1.3.6 Geodetector

Geodetector is a set of statistical methods for detecting spatial heterogeneity and revealing its underlying driving forces. It includes four modules: factor detector, interaction detector, risk detector, and ecological detector [21]. The factor detector analyzes the spatial heterogeneity of data and the explanatory

power of factors for the spatial heterogeneity of the data. The calculation formula is:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (11)$$

where:  $L$  is the number of subsets;  $N$  and  $\sigma^2$  represent the total sample size and variance;  $N_h$  and  $\sigma_h^2$  represent the sample size and variance of subset  $h$ , respectively;  $q \in [0, 1]$ , and a larger  $q$  value indicates more pronounced spatial differentiation in the data. The interaction detector identifies interactions among different risk factors  $X$ , that is, it evaluates the change in the explanatory power for the dependent variable  $Y$  when factors  $X_1$  and  $X_2$  act jointly. The relationship between two factors can be divided into five types (Table 1).

**Table 1 Types of interactions between two independent variables on the dependent variable**

**Tab. 1 Types of interaction between two covariates**

| Interaction                       | Judgment criterion                                              |
|-----------------------------------|-----------------------------------------------------------------|
| Nonlinear weakening               | $q(X_1 \cap X_2) < \min[q(X_1), q(X_2)]$                        |
| Single-factor nonlinear weakening | $\min[q(X_1), q(X_2)] < q(X_1 \cap X_2) < \max[q(X_1), q(X_2)]$ |
| Two-factor enhancement            | $q(X_1 \cap X_2) > \max[q(X_1), q(X_2)]$                        |
| Independent                       | $q(X_1 \cap X_2) = q(X_1) + q(X_2)$                             |
| Nonlinear enhancement             | $q(X_1 \cap X_2) > q(X_1) + q(X_2)$                             |

## 2 Results and Analysis

### 2.1 Determination of evaluation scales for LUI and LER

When raster data are resampled, land patches may show area fluctuations during pixel merging; if oversampling occurs, the stability and connectivity of patches will be affected. In this study, sampling was conducted at 10 m intervals within the range of 30–150 m to obtain 13 spatial grains, and area information entropy and area information loss were calculated separately. The results show that, at 80 m, the area information entropy is greater than 0.42, and area information loss increases rapidly when the grain is greater than 80 m (Fig. 2). Therefore, considering the variation characteristics of area information entropy and area information loss, the spatial grain selected in this paper is 80 m.

*Figure annotations: legend—area information loss; area information entropy; x-axis—spatial grain/m; left y-axis—area information loss/%; right y-axis—area information entropy.*

**Figure 2 Area information loss and area information entropy at different spatial grains**

**Fig. 2 Area information loss and information entropy at different spatial grains**

On the basis of the spatial-grain analysis, the land-use data at 80 m resolution were divided, using multiple intervals from 0.5 to 16 km, into regular evaluation units at six scales, and the land use intensity index and landscape...

landscape ecological risk index, and fitted the parameters of the semi-variogram function (Gaussian function) for the two, obtaining the nugget-to-sill ratio and accuracy, so as to preliminarily screen an appropriate evaluation scale. The analysis found that near 8 km, the nugget-to-sill ratio was relatively small and the fitting accuracy was high. Further fitting was conducted by constructing 10 spatial extents at 1 km intervals within the range of 5–14 km (Table 2). The results show that, at the 10 km scale, the land-use intensity index had the smallest nugget-to-sill ratio and fitting accuracy; for the landscape ecological risk index, the nugget-to-sill ratio was smallest at the 11 km scale, and the standardized root mean square error was relatively good. Therefore, this paper selects a spatial extent of 10.5 km to calculate the land-use intensity and landscape ecological risk indices.

## 2.2 Evaluation of LUI and LER and Calculation of CCD

Based on the results of the spatial-scale analysis, the land-use intensity index, the landscape ecological risk index, and the coupling coordination degree between the two were calculated, and their spatiotemporal variation characteristics were analyzed.

### 2.2.1 Spatiotemporal Variation Characteristics of LUI

The land-use intensity types in Xinjiang were mainly dominated by low intensity (Fig. 3). From 2003 to 2023, they mainly shifted out of low and medium intensity and into relatively low, relatively high, and high intensity, with the rate showing a gradual slowing trend. Compared with 2003, in 2013 and 2023 the area of low-intensity zones decreased by 28276.4 km<sup>2</sup> and 16407.7 km<sup>2</sup>, accounting for 1.73% and 1.01%, respectively; the area of relatively low-intensity zones continued to increase, by 9095.8 km<sup>2</sup> and 18730.3 km<sup>2</sup>, accounting for 0.56% and 1.15%, respectively; the area of medium-intensity zones decreased by 9749.6 km<sup>2</sup> and 12231.6 km<sup>2</sup>, accounting for 0.60% and 0.75%, respectively; the area of relatively high-intensity zones first decreased by 352.4 km<sup>2</sup> and then increased by 1747.3 km<sup>2</sup>, accounting for 0.02% and 0.11%, respectively; and the area of high-intensity zones increased by 29282.3 km<sup>2</sup> and 8161.7 km<sup>2</sup>, accounting for 1.80% and 0.50%, respectively. Spatially (Fig. 4a–Fig. 4c), land-use intensity in the study area generally decreased gradually with increasing distance from the northern slope of the Tianshan Mountains, the edge of the Taklimakan Desert, the Ili River Valley region, and the northern part of the Tacheng region. Areas with increasing high intensity were mainly concentrated on the northern slope of the Tianshan Mountains, the Ili River Valley, and Aksu,

Korla, and Kashgar in southern Xinjiang, while growth in eastern Xinjiang was relatively slow.

### 2.2.2 Spatiotemporal Variation Characteristics of LER

The landscape ecological risk types in Xinjiang were mainly dominated by the high-risk level (Fig. 5). From 2003 to 2023, except for relatively low risk, the areas of other types first increased and then decreased, mainly shifting from high and medium risk to relatively low, relatively high, and low risk. Compared with 2003, in 2013 and 2023 the area of low risk increased by 25977.6 km<sup>2</sup> and 3242.7 km<sup>2</sup>, accounting for 1.59% and 0.20%, respectively; the area of relatively low risk increased by 8219.8 km<sup>2</sup> and 5736.4 km<sup>2</sup>, accounting for 0.50% and 0.35%, respectively; the area of medium risk decreased by 4729.5 km<sup>2</sup> and 12721.9 km<sup>2</sup>, accounting for 0.29% and 0.78%, respectively; the area of relatively high risk increased by 1849.5 km<sup>2</sup> and 7246.6 km<sup>2</sup>, accounting for 0.11% and 0.44%, respectively; and the area of high risk decreased by 24337.2 km<sup>2</sup> and 17474.8 km<sup>2</sup>, accounting for 1.49% and 1.07%, respectively. Spatially (Fig. 4d-Fig. 4f), zones of medium risk and above were mainly distributed in the Tuha Basin, the Tarim Basin, and the Junggar Basin. Low-risk zones occurred in the urban agglomeration on the northern slope of the Tianshan Mountains, the Ili River Valley region, southwestern Altay, and Kashgar City, Aksu City, Korla City, and the XPCC division cities along the edge of the Tarim Basin. Xinjiang is located in China's arid and semi-arid regions, with a large area of unused land and strong connectivity. Because precipitation is scarce and vegetation is sparse, the landscape ecology is fragile; agricultural and urban areas change surface cover through crop planting, urban greening, and other means, thereby reducing landscape ecological risk.

### 2.2.3 Spatiotemporal Variation Characteristics of CCD

From 2003 to 2023, the mean coupling degrees were 0.31, 0.30, and 0.29, respectively. According to the coupling-degree classification principle [14], the whole region was between the antagonistic stage and the run-in stage. The coordination degree ranged from 0.205 to 0.501, with mean values of 0.425, 0.428, and 0.431, respectively, showing an increasing trend. From 2003 to 2023, the overall coupling coordination degree was less than 0.7, and the mean value was less than 0.26, showing a trend of first decreasing and then increasing. Using intervals of 0.2, 0.4, 0.6, and 0.8, the coupling coordination degree was divided into severe imbalance, mild imbalance, primary coordination, good coordination, and high-quality coordination (Fig. 6). The areas of severe imbalance and primary coordination gradually decreased, while the areas of mild imbalance and good coordination gradually

**Table 2 Analysis results of the semi-variogram at different spatial extents**

**Tab. 2 Analysis results of the semi-variogram at different spatial**

## extents

|     |                           |                       |                          |                             |                           | Standardized<br>root<br>mean<br>square<br>error |
|-----|---------------------------|-----------------------|--------------------------|-----------------------------|---------------------------|-------------------------------------------------|
|     | Spatial<br>ex-<br>tent/km | Nugget<br>value       | Partial<br>sill<br>value | Nugget-<br>to-sill<br>ratio | Range/kmsquare/ $10^{-2}$ | Root<br>mean<br>square<br>error                 |
| LUI | 8                         | $1.01 \times 10^{-1}$ | $7.75 \times 10^{-1}$    | 0.211                       | 39029.11                  | 1.63                                            |
| LUI | 9                         | $9.39 \times 10^{-2}$ | $6.62 \times 10^{-1}$    | 0.205                       | 39848.01                  | 1.60                                            |
| LUI | 10                        | $8.89 \times 10^{-2}$ | $7.73 \times 10^{-1}$    | 0.193                       | 41440.84                  | 1.59                                            |
| LUI | 11                        | $8.47 \times 10^{-2}$ | $5.55 \times 10^{-1}$    | 0.193                       | 41768.57                  | 1.65                                            |
| LUI | 12                        | $8.88 \times 10^{-2}$ | $4.46 \times 10^{-1}$    | 0.204                       | 43962.20                  | 1.74                                            |
| LER | 8                         | $8.71 \times 10^{-5}$ | $3.36 \times 10^{-4}$    | 0.206                       | 40943.23                  | 0.94                                            |
| LER | 9                         | $5.12 \times 10^{-4}$ | $1.05 \times 10^{-2}$    | 0.200                       | 42037.35                  | 0.96                                            |
| LER | 10                        | $7.99 \times 10^{-5}$ | $2.23 \times 10^{-4}$    | 0.198                       | 43296.10                  | 0.97                                            |
| LER | 11                        | $7.68 \times 10^{-5}$ | $1.13 \times 10^{-4}$    | 0.197                       | 44009.34                  | 1.01                                            |
| LER | 12                        | $7.65 \times 10^{-5}$ | $1.02 \times 10^{-4}$    | 0.202                       | 44943.74                  | 1.03                                            |

**Fig. 3** Area changes among different types and mean LUI in Xinjiang, 2003–2023

Visible chart labels: Low intensity; relatively low intensity; moderate intensity; relatively high intensity; high intensity; LUI; area /  $10^4 \text{ km}^2$ ; 2003; 2013; 2023.

gradually increased. Compared with 2003, the area of severe imbalance in 2013 and 2023 decreased by  $4583.8 \text{ km}^2$  and  $15512.6 \text{ km}^2$ , accounting for 0.28% and 0.95%, respectively; the area of mild imbalance increased by  $21427.9 \text{ km}^2$  and  $38826.7 \text{ km}^2$ , accounting for 1.31% and 2.38%; the area of primary coordination continued to decrease, by  $18718.3 \text{ km}^2$  and  $26070.3 \text{ km}^2$ , accounting for 1.15% and 1.60%; and the area of good coordination continued to increase, by  $1874.2 \text{ km}^2$  and  $2756.2 \text{ km}^2$ , accounting for 0.11% and 0.17%. Spatially (Fig. 7a–Fig. 7c), areas with low coordination were mainly distributed in regions with high population density, whereas areas with high coordination were mainly concentrated in deserts, Gobi areas, and other regions with low land-use intensity and high landscape risk. The primary- and good-coordination areas of coupling coordination were mainly distributed in the oasis zones along the desert margins

of southern Xinjiang, where human activities are frequent, the urban agglomeration on the northern slope of the Tianshan Mountains, the Ili River Valley, and northern Tacheng; the severely imbalanced areas were mainly in the Turpan-Hami Basin, Tarim Basin, and Junggar Basin (Fig. 7d–Fig. 7f).

### 3 Discussion

#### 3.1 Spatial heterogeneity analysis of CCD

From 2003 to 2023, the global Moran' s index of the coupling coordination degree first increased and then decreased; overall, it was greater than 0.8, indicating significant clustering characteristics (Table 3). Local Moran' s index analysis showed that Low-High and High-Low cluster areas were very few. Compared with 2003, the areas of High-High clusters in 2013 and 2023 decreased by 39289.7 km<sup>2</sup> and 28399.7 km<sup>2</sup>, accounting for 2.41% and 1.74%, respectively; the areas of Low-Low clusters increased by 9891.5 km<sup>2</sup> and 599.9 km<sup>2</sup>, accounting for 2.41% and 1.74%; and the areas with no spatial correlation increased by 30124.1 km<sup>2</sup> and 27020.9 km<sup>2</sup>, accounting for 1.85% and 1.66%. Spatially, High-High clusters were mainly located in northwestern Xinjiang, along the southern margin of the Tarim Basin, the foothills on both sides of the Tianshan Mountains, and population-gathering areas in the Altay region. Overall, they formed an “E” -shaped distribution pattern with more clusters in the northwest and fewer in the southeast, characterized by “three horizontal bands and one vertical band.” Low-Low clusters were mainly distributed in the Tarim Basin, the Turpan-Hami Basin, and the Junggar Basin. Spatially uncorrelated areas were mainly in mountainous areas and basin margins with relatively small populations (Fig. 8). Overall, High-High clusters continued to shrink and disperse, and their connectivity decreased, indicating that Xinjiang' s development mode is transforming and that areas of economic and social development are becoming more concentrated.

#### 3.2 Characteristics of LUI and LER in different coupling-coordination type zones

The normalized mean values of the land-use intensity index and landscape ecological risk index among different coupling-coordination types from 2003 to 2023 show that,

**Fig. 4** Spatial distribution of LUI and LER in Xinjiang, 2003–2023

Visible panel labels: (a) 2003; (b) 2013; (c) 2023; (d) 2003; (e) 2013; (f) 2023.

Visible map legends:

LUI—low intensity; relatively low intensity; moderate intensity; relatively high intensity; high intensity.

LER—low risk; relatively low risk; moderate risk; relatively high risk; high risk.

**Fig. 5** Changes in mean LER and in the areas of different risk levels in Xinjiang, 2003–2023.

Legend: low risk; relatively low risk; medium risk; relatively high risk; high risk; LER.

Axes: area /  $10^4 \text{ km}^2$ ; LER. Years: 2003, 2013, 2023.

**Fig. 6** Changes in mean CCD and in the areas of different coupling-coordination types in Xinjiang, 2003–2023.

Legend: severe maladjustment; mild maladjustment; primary coordination; good coordination; high-quality coordination; CCD.

Axes: area /  $10^4 \text{ km}^2$ ; CCD. Years: 2003, 2013, 2023.

As the level of coupling coordination increased, the land-use intensity index continuously increased, while the landscape ecological risk index continuously decreased (Fig. 9). In severely maladjusted areas, the land-use intensity index was close to 0 and the landscape ecological risk index was close to 1; whereas in well-coordinated areas, the mean values of the land-use intensity index and the landscape ecological risk index were both around 0.40 and were the closest to one another. Clearly, in areas of human activity, the land-use intensity index was relatively high while the landscape ecological risk index was relatively low; together, the two promoted the improvement of coupling coordination. In desert areas, however, the landscape ecological risk index was high and the land-use intensity index was low, resulting in the lowest coupling coordination degree. In 2003, 2013, and 2023, the differences in the mean land-use intensity between the good-coordination and severe-maladjustment areas were 0.30, 0.33, and 0.36, respectively, while the mean landscape ecological risk index

**Fig. 7** Spatial distribution of coupling degree, coordination degree, and coupling coordination in Xinjiang, 2003–2023.

Subpanels:

(a) 2003; (b) 2013; (c) 2023.

(d) 2003; (e) 2013; (f) 2023.

(g) 2003; (h) 2013; (i) 2023.

Each map includes a north arrow (N) and a scale bar of 0–360 km.

Legend for coupling degree: low-coupling stage; antagonistic stage; adjustment stage; high-coupling stage.

Legend for coordination degree: extreme maladjustment; severe maladjustment; moderate maladjustment; mild maladjustment; near-maladjustment; reluctant coordination.

Legend for coupling coordination degree: severe maladjustment; mild maladjustment; primary coordination; good coordination; high-quality coordination.

respectively decreased by  $-0.48$ ,  $-0.53$ , and  $-0.55$ , indicating that landscape ecological risk in different coupling-coordination zones contributed more to the improvement of coupling coordination than did land-use intensity.

**Table 3 Global Moran' s  $I$  of the CCD in Xinjiang, 2003–2023**

**Tab. 3 Moran' s  $I$  of the CCD in Xinjiang from 2003 to 2023**

| Year | Moran' s $I$ | $Z$ -score | $P$    |
|------|--------------|------------|--------|
| 2003 | 0.844        | 145.09     | 0.00** |
| 2013 | 0.847        | 145.72     | 0.00** |
| 2023 | 0.843        | 144.93     | 0.00** |

Note: \*\* indicates significance at the 1% level.

### 3.3 Analysis of CCD Driving Factors

The factor-detection results of the geographical detector show (Fig. 10) that, from 2003 to 2023, the effects of all factors on coupling coordination across Xinjiang were significant, with  $P$ -values far below 0.01. The primary factor affecting coupling coordination was NDVI in all years, with  $q$ -values greater than 0.5. Spatially, NDVI in Xinjiang has an obvious

**Figure 8 labels:** (a) 2003; (b) 2013; (c) 2023. Legend: High-high cluster; High-low cluster; Low-high cluster; Low-low cluster; Not significant.

#### Fig. 8 LISA cluster map for CCD in Xinjiang from 2003 to 2023

**Figure 9 labels:** Legend: LUI; LER; CCD. Years: 2003; 2013; 2023. Coupling-coordination types: Severe imbalance; Mild imbalance; Primary coordination; Good coordination. Vertical axis: Mean value of each index. Horizontal axis: Coupling-coordination type.

#### Fig. 9 Mean LUI and mean LER in different coupling coordination type zones in Xinjiang from 2003 to 2023

**Figure 10 labels:** Legend: 2003; 2013; 2023. Vertical axis: Coupling coordination degree. Horizontal axis: Driving factors. Driving factors: NDVI; GDP; Distance to residential land; Distance to roads; Distance to rivers; Population density; Precipitation; Nighttime lights; Potential evapotranspiration; Snow-cover days; Air temperature; Elevation; Slope.

#### Fig. 10 Factor detection results for CCD in Xinjiang from 2003 to 2023

The spatial clustering is obvious: NDVI values are low in desert-Gobi areas, whereas they are high in mountain grasslands and forested areas. In oases and river-valley regions with frequent human activities, agricultural activities and urban construction also make NDVI relatively high. These factors create a strong relationship between NDVI levels and regional development, and therefore NDVI has the strongest explanatory power. Factors with  $q$  values exceeding 0.2 include GDP, settlements, roads, rivers, population density, and precipitation; factors below 0.2 are nighttime lights, potential evapotranspiration, snow-cover days, temperature, elevation, and slope. Except for NDVI, the coupling coordination degree is mainly affected by socioeconomic factors. The impact

of human activities on surface landscapes has caused changes in land cover; increases in construction land and agricultural land have strengthened land-use intensity, while increases in cultivated crops and ecological green spaces planted by humans have reduced ecological risk, thereby improving the coupling coordination degree. Temporally, the  $q$  values of socioeconomic factors first increase and then decrease, or continue to increase; among natural factors, except for NDVI, which first increases and then decreases, the other factors continue to decline. In Xinjiang, natural factors such as potential evapotranspiration, temperature, precipitation, and elevation do not change markedly in the short term and have limited influence on the coupling coordination degree. The explanatory power of GDP and nighttime lights increases more obviously than that of settlements, roads, and rivers, which is consistent with Xinjiang's development trend around 2013. Overall, the spatiotemporal variation in the coupling coordination degree is driven by multiple factors; the explanatory power of natural factors gradually weakens, whereas that of economic factors gradually strengthens.

The interaction-factor detection results show (Fig. 11) that the explanatory power of interactions among factors for the coupling coordination degree is significantly greater than that of any single factor, exhibiting nonlinear enhancement or two-factor enhancement. From 2003 to 2023, the interaction between NDVI and other factors had the strongest explanatory power, with  $q$  values generally higher than 0.5. Socioeconomic factors were generally higher than natural factors; the interactive explanatory power of GDP and other factors—especially nighttime lights—changed markedly, with  $q$  values around 0.4. The interactive explanatory power among natural factors such as rivers, potential evapotranspiration, temperature, and slope was relatively weak. Overall, from 2003 to 2023, the coupling coordination degree first decreased and then increased, but remained lower than in the initial year. This indicates that the achievements of China's ecological-civilization construction have already become evident. In Xinjiang's future economic and social development, ecological security should continue to receive attention, and ecological-civilization construction should be maintained.

### 3.4 Analysis of CCD Changes in Prefecture-Level Cities and XPCC Division-Level Cities

A comparison of the mean land-use intensity index, landscape ecological risk index, and coupling coordination degree in Xinjiang's prefecture-level cities and XPCC division-level cities in 2003 shows (Fig. 12) that Shihezi City, Shuanghe City, Huyanghe City, Baiyang City, Kokdala City, and other places with relatively high coupling coordination degrees have landscape ecological risk indices and land-use intensity indices that are closer to each other. XPCC cities have small areas and rapid economic development, and their landscape ecological risk and land-use intensity indices are relatively high, resulting in higher coupling coordination degrees. By contrast, large administrative regions such as Bayingolin Prefecture, Hotan Prefecture, and Hami City have large desert areas, relatively

low economic development, large differences between land-use intensity indices and landscape ecological risk indices, and therefore lower coupling coordination degrees. Ili Prefecture, Bortala Prefecture, Karamay, Urumqi, and Tacheng Prefecture, which are relatively intermediate between the two types, have comparatively small areas and less unused land, and are located in the economic belt on the northern slope of the Tianshan Mountains; their land-use intensity indices and landscape ecological risk indices change relatively steadily, and their coupling coordination degrees are moderate.

Statistics of the mean coupling coordination degree of Xinjiang's prefecture-level cities and XPCC division-level cities from 2003 to 2023 show (Fig. 13) that, because XPCC division-level cities have a high degree of mechanization and small regional areas, their mean coupling coordination degrees are all higher than 0.4 except for Xinxing City, which was established relatively late. Except for Baiyang City and Xinxing City, where the coupling coordination degree first increased and then decreased, all other division-level cities show gradual increases, although the growth rate slows. Among prefecture-level cities, all are below 0.4 except Ili Prefecture and Bortala Prefecture; Turpan City, Bayingolin Prefecture, Hotan Prefecture, and Hami City are even below 0.2. Compared with the XPCC, local areas show greater variation in coupling coordination degree due to differences in regional area and economic development, together with the influence of locational advantages and policies, making the changes appear even more

**Fig. 11 Factor interaction detection results for CCD in Xinjiang from 2003 to 2023**

Figure panels: 2003, 2013, 2023. Variables shown include elevation, potential evapotranspiration, GDP, snow-cover days, settlements, nighttime lights, population density, precipitation, distance to roads, slope, distance to rivers, temperature, and NDVI. Color scale:  $q$  value, from 0.05 to 0.69.

**Fig. 12 Comparison of mean LUI, LER, and CCD by prefectures and XPCC divisions in Xinjiang**

**Fig. 13 Changes in mean CCD by prefectures and XPCC divisions in Xinjiang from 2003 to 2023**

The patterns were diverse: Ili Prefecture, Urumqi City, Changji Prefecture, and Hami City gradually declined; Bortala Prefecture, Kizilsu Prefecture, Turpan City, and Bayingolin Prefecture first decreased and then increased; Karamay City and Altay Prefecture first increased and then decreased; only Kashgar Prefecture and Aksu Prefecture continued to increase.

Overall, the coupling coordination degree of different prefectures, divisions, and cities in Xinjiang showed the following characteristics. First, regions with relatively developed economies and smaller areas had higher coupling coordination degrees, fewer type transitions, and generally developed toward good coordination, such as XPCC divisions/cities, Urumqi City, and Karamay City. Such

regions can maintain their existing development mode while paying attention to ecological protection, thereby achieving sustainable development. Second, regions with slower development and larger areas had lower coupling coordination degrees, generally fluctuating between primary coordination and mild imbalance, such as Changji Prefecture, Hami City, Hotan City, and Bayingolin Prefecture. For these regions, their vast areas contain great potential, and more investment can subsequently be made according to local characteristics. Third, against the broader background of establishing cities at XPCC division headquarters and promoting southward development, newly established division-level cities such as Xinxing City, Baiyang City, and Kunyu City, as well as Aksu Prefecture and Kashgar Prefecture, developed relatively rapidly, with faster growth in coupling coordination degree. Given their rapid development, greater attention should be paid to ecological issues, and ecological security should be emphasized while pursuing economic development. Fourth, regional differences among southern, northern, and eastern Xinjiang were pronounced, with the coupling coordination degree following the order northern Xinjiang > southern Xinjiang > eastern Xinjiang. In planning, the government should further attend to the problem of development imbalance in severely imbalanced regions and reduce regional development disparities through more policy guidance, such as southward development.

## 4 Conclusion

Based on land-use data, this study analyzed the spatiotemporal changes in land-use intensity, landscape ecological risk, and their coupling coordination in Xinjiang, and further explored the spatiotemporal differentiation of coupling coordination degree, the characteristics of land-use intensity and landscape ecological risk under different coupling coordination types, the driving factors, and differences among administrative regions. The main conclusions are as follows:

- (1) The overall coupling coordination degree in Xinjiang was relatively low, showing a trend of first decreasing and then increasing. Primary and good coordination areas were concentrated in regions with intensive human activities, displaying a pattern of higher values in the northwest and lower values in the southeast. High-high clusters exhibited an “E”-shaped spatial distribution pattern and became increasingly concentrated.
- (2) Land-use intensity and landscape ecological risk differed greatly among different coupling coordination zones, and changes in landscape ecological risk were stronger than those in land use

intensity.

- (3) Human socioeconomic activities are the main driving factors behind changes in coupling coordination; among them, changes in the explanatory power of GDP and nighttime lights are the most evident.
- (4) Influenced by regional area, current economic conditions, and policies, the

degree of coupling coordination differs markedly: the Corps > localities; small-area prefecture-level cities > large-area prefecture-level cities; Northern Xinjiang > Southern Xinjiang > Eastern Xinjiang.

With the promotion of the southward-development policy, as well as the implementation of scientific land-use planning and environmental protection measures, interregional differences have been reduced. The coupling coordination between land-use intensity and landscape ecological risk has begun to strengthen, and socioeconomic development is gradually moving toward an intensive, high-quality, and green development path. Future development should take regional characteristics into account, safeguard ecological security while pursuing economic development, and continuously promote coordinated and sustainable regional development.

## References:

- [1] Guan Yiheng, Meng Mei, Yang Songxiao, et al. Coordinated development and multi-scenario simulation of land-use intensity and carbon emissions in Xinjiang[J]. *Arid Zone Research*, 2025, 42(8): 1501-1513. [Guan Yiheng, Meng Mei, Yang Songxiao, et al. Coordinated development and multi-scenario simulation of land use intensity and carbon emissions in Xinjiang[J]. *Arid Zone Research*, 2025, 42(8): 1501-1513.]
- [2] Liu Fang, Yan Huimin, Liu Jiyuan, et al. Spatial distribution pattern of land-use intensity in China at the beginning of the 21st century[J]. *Acta Geographica Sinica*, 2016, 71(7): 1130-1143. [Liu Fang, Yan Huimin, Liu Jiyuan, et al. Spatial pattern of land use intensity in China in 2000[J]. *Acta Geographica Sinica*, 2016, 71(7): 1130-1143.]
- [3] Zhuang Dafang, Liu Jiyuan. Study on the model of regional differentiation of land-use degree in China[J]. *Journal of Natural Resources*, 1997, 12(2): 10-16. [Zhuang Dafang, Liu Jiyuan. Study on the model of regional differentiation of land use degree in China[J]. *Journal of Natural Resources*, 1997, 12(2): 10-16.]
- [4] Hu Hebing, Liu Hongyu, Hao Jinfeng, et al. Spatio-temporal differentiation characteristics of ecosystem service value in an urbanized watershed and its response to land-use degree[J]. *Acta Ecologica Sinica*, 2013, 33(8): 2565-2576. [Hu Hebing, Liu Hongyu, Hao Jinfeng, et al. Spatio-temporal variation in the value of ecosystem services and its response to land use intensity in an urbanized watershed[J]. *Acta Ecologica Sinica*, 2013, 33(8): 2565-2576.]
- [5] Yuan Xuefeng, Zhang Ruina, Li Linru. Spatial network analysis of coupling coordination between land-use intensity and habitat quality in the Loess Plateau of Northern Shaanxi[J/OL]. *Environmental Science*, 2026, 1-14. [Yuan Xuefeng, Zhang Ruina, Li Linru. Spatial network analysis of coupling coordination between land use intensity and habitat quality in the Loess Plateau of Northern Shaanxi[J/OL]. *Environmental Science*, 2026, 1-14.]

- [6] Cao Qiwen, Zhang Xiwen, Ma Hongkun, et al. Review of landscape ecological risk research and an assessment framework based on ecosystem services: ESRISK[J]. *Acta Geographica Sinica*, 2018, 73(5): 843-855. [Cao Qiwen, Zhang Xiwen, Ma Hongkun, et al. Review of landscape ecological risk and an assessment framework based on ecological services: ESRISK[J]. *Acta Geographica Sinica*, 2018, 73(5): 843-855.]
- [7] Peng Jian, Dang Weixiong, Liu Yanxu, et al. Review and prospects of landscape ecological risk assessment research[J]. *Acta Geographica Sinica*, 2015, 70(4): 664-677. [Peng Jian, Dang Weixiong, Liu Yanxu, et al. Review on landscape ecological risk assessment[J]. *Acta Geographica Sinica*, 2015, 70(4): 664-677.]
- [8] Wang Juan, Cui Baoshan, Liu Jie, et al. Effects of land use and its changes on landscape ecological risk in the Lancang River Basin of Yunnan[J]. *Acta Scientiae Circumstantiae*, 2008, 28(2): 269-277. [Wang Juan, Cui Baoshan, Liu Jie, et al. The effect of land use and its change on ecological risk in the Lancang River watershed of Yunnan Province at the landscape scale[J]. *Acta Scientiae Circumstantiae*, 2008, 28(2): 269-277.]
- [9] Si Qi, Fan Haoran, Dong Wenming, et al. Landscape ecological risk assessment and prediction for the Yarkant River Basin, Xinjiang[J]. *Arid Zone Research*, 2024, 41(4): 684-696. [Si Qi, Fan Haoran, Dong Wenming, et al. Landscape ecological risk assessment and prediction for the Yarkant River Basin, Xinjiang, China[J]. *Arid Zone Research*, 2024, 41(4): 684-696.]
- [10] Ma Shiyong, Chen Ying, Pei Tingting. Landscape ecological risk assessment in Lanzhou City based on land-use change[J]. *Territory & Natural Resources Study*, 2023, 45(6): 31-36. [Ma Shiyong, Chen Ying, Pei Tingting. Landscape ecological risk assessment in Lanzhou City based on land use change[J]. *Territory & Natural Resources Study*, 2023, 45(6): 31-36.]
- [11] Xiu Yangjing, Hou Mengjing, Tian Jiaoyang, et al. Characteristics of spatio-temporal variation in landscape ecological risk in Gansu Province based on land use/cover[J]. *Acta Prataculturae Sinica*, 2023, 32(1): 1-15. [Xiu Yangjing, Hou Mengjing, Tian Jiaoyang, et al. Characteristics of temporal and spatial variation in landscape ecological risk in Gansu Province based on land use and cover[J]. *Acta Prataculturae Sinica*, 2023, 32(1): 1-15.]
- [12] Cong Xiaonan. Expression and properties of the coupling-degree model and several misuses in geography[J]. *Economic Geography*, 2019, 39(4): 18-25. [Cong Xiaonan. Expression and mathematical property of Coupling Model, and its misuse in geographical science[J]. *Economic Geography*, 2019, 39(4): 18-25.]
- [13] Illingworth V. *The Penguin Dictionary of Physics*[M]. Beijing: Foreign Language Press, 1996.
- [14] Guo Shanshan. Research on the coupling coordination between ecosystem health and urbanization in the Yellow River Basin[D]. Xuzhou: China University of Mining and Technology (Xuzhou), 2022. [Guo Shanshan. Research on the

Coupling and Coordination of Ecosystem Health and Urbanization in the Yellow River Basin[D]. Xuzhou: China University of Mining and Technology, 2022.]

[15] Wang Youfeng. Landscape ecological risk assessment and analysis of its coupling characteristics in Fugu County, Northern Shaanxi[J]. *Environmental Ecology*, 2024, 6(9): 23–32. [Wang Youfeng. Landscape ecological risk assessment and its coupling characteristics analysis in Fugu County, Northern Shaanxi[J]. *Environmental Ecology*, 2024, 6(9): 23–32.]

[16] Zhang Yan, Zhang Shaojuan, Lyu Tao, et al. Research on the coupling and synergistic relationship between landscape ecological risk and habitat quality in the Yellow River Basin (Inner Mongolia section)[J]. *Ecology and Environmental Sciences*, 2025, 34(12): 1841–1852. [Zhang Yan, Zhang Shaojuan, Lyu Tao, et al. Research on the coupling and synergistic relationship between landscape ecological risk and habitat quality in the Yellow River Basin

(Inner Mongolia Section)[J]. *Ecology and Environmental Sciences*, 2025, 34(12): 1841–1852.]

[17] Li S C, Bing Z L, Jin G. Spatially explicit mapping of soil conservation service in monetary units due to land use/cover change for the Three Gorges Reservoir Area, China[J]. *Remote Sensing*, 2019, 11(4): 468.

[18] Kang Ziwei, Zhang Zhengyong, Wei Hong, et al. Landscape ecological risk assessment in the Manas River Basin based on land-use change[J]. *Acta Ecologica Sinica*, 2020, 40(18): 6472–6485. [Kang Ziwei, Zhang Zhengyong, Wei Hong, et al. Landscape ecological risk assessment in Manas River Basin based on land use change[J]. *Acta Ecologica Sinica*, 2020, 40(18): 6472–6485.]

[19] Yang Rongqin, Xiao Yulei, Chi Miaomiao, et al. Temporal and spatial variations of human activities and landscape ecological risks in the Tarim River Basin, China, during the last 20 years[J]. *Arid Zone Research*, 2024, 41(6): 1010–1020. [Yang Rongqin, Xiao Yulei, Chi Miaomiao, et al. Temporal and spatial variations of human activities and landscape ecological risks in the Tarim River Basin, China, during the last 20 years[J]. *Arid Zone Research*, 2024, 41(6): 1010–1020.]

[20] Song Changying, Sun Haojie, Xu Xueting, et al. Landscape ecological risk assessment and spatiotemporal evolution analysis in the Ili River Valley[J]. *Forest Inventory and Planning*, 2025, 50(2): 92–101. [Song Changying, Sun Haojie, Xu Xueting, et al. Landscape ecological risk assessment and spatial and temporal evolution in Ili River Valley[J]. *Forest Inventory and Planning*, 2025, 50(2): 92–101.]

[21] Wang Jinfeng, Xu Chengdong. Geodetector: Principle and prospect[J]. *Acta Geographica Sinica*, 2017, 72(1): 116–134. [Wang Jinfeng, Xu Chengdong. Geodetector: Principle and prospective[J]. *Acta Geographica Sinica*, 2017, 72(1): 116–134.]

# Coupling and coordination analysis of land use intensity and landscape ecological risk in Xinjiang

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**Abstract:** Xinjiang is located in the arid region of Northwest China and faces growing tensions between socioeconomic development and ecological conservation under the Belt and Road Initiative and the strategy of southward development. Using land-use data from 2003, 2013, and 2023, this study determined the optimal spatial grain (80 m) and extent (10.5 km) for assessing land use intensity (LUI) and landscape ecological risk (LER). Based on these scales, we calculated the LUI and LER indices, evaluated their coupling coordination degree (CCD), and analyzed the spatiotemporal evolution of CCD. The results show that: (1) Areas with high LUI, low LER, and high CCD were predominantly concentrated in the northern slope of the Tianshan Mountains, the Ili River Valley, and the oasis zones of the Taklimakan Desert—regions characterized by intensive human activities. (2) From 2003 to 2023, LUI exhibited an overall upward trend, while LER decreased. The CCD initially declined and then increased, remaining below 0.7. Spatially, areas of severe imbalance and primary coordination gradually shrank, while areas of mild imbalance and good coordination expanded. (3) High-high clustering of CCD displayed an “E” - shaped pattern, with higher values in the northwest and lower values in the southeast. Across different CCD types, changes in LER were more pronounced than those in LUI. (4) Socioeconomic factors (e.g., GDP and nighttime light intensity) had stronger explanatory power than natural factors. The CCD of prefectures and cities was jointly influenced by natural endowment, economic development, and policy interventions, with the most significant changes observed in the Xinjiang Production and Construction Corps and southern Xinjiang.

**Keywords:** scale effect; land use intensity; landscape ecological risk; coupling coordination degree; spatial heterogeneity; Geodetector

*Note: Figure translations are in progress. See original paper for figures.*

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